

Predictive analytics in Sensor (IoT) Data



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Institute for Computer Science and Control

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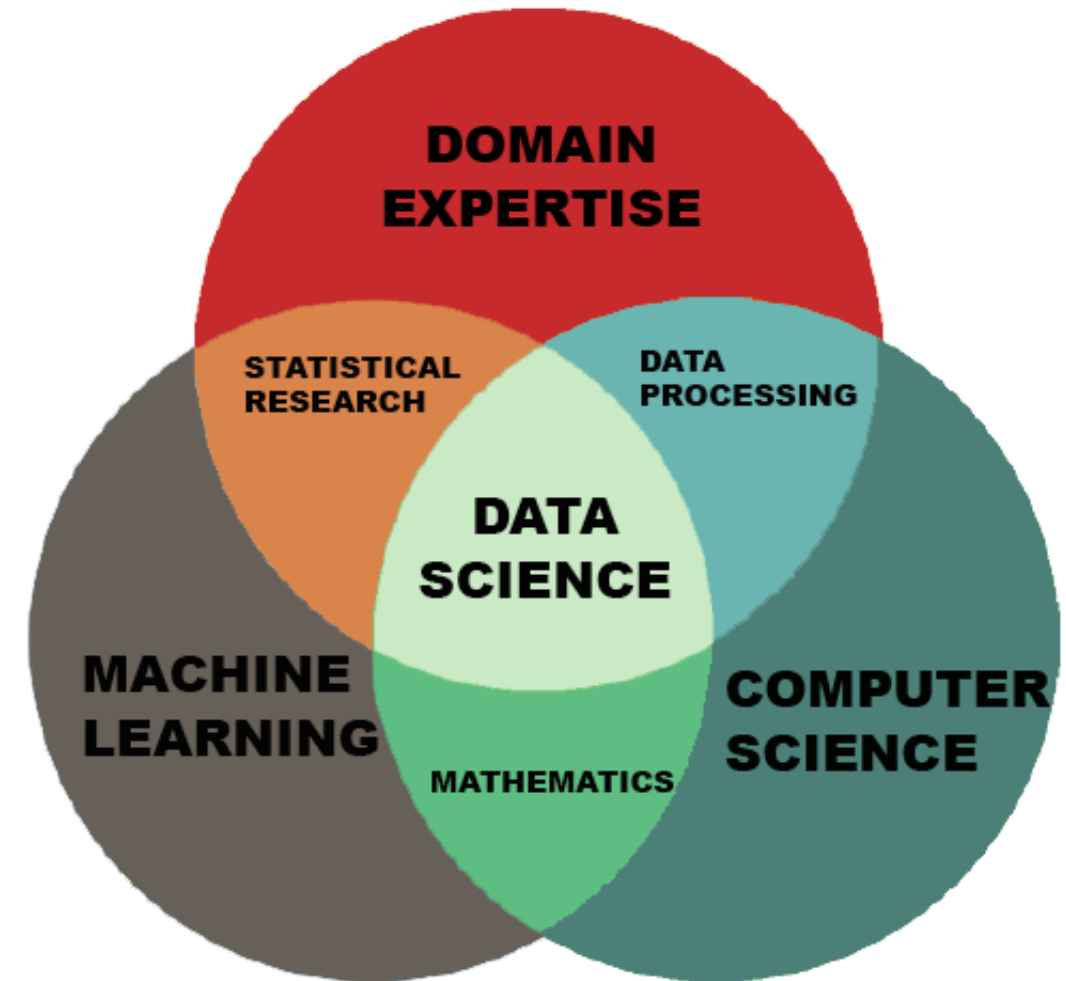
Big Data – Lendület kutatócsoport

- Összesen 6 műszaki/informatika Lendület csoport
- Lendület támogatás a költségvetés ~15%-a, ~ 40% közvetlen szerződés, 20-20% hazai és EU, 5% SZTAKI belső erőforrás
- Teljes innovációs lánc, kutatástól alkalmazásokig



Alkalmazási területeink

- AEGON
 - 40 millió ügyfélrekord duplikátum-mentesítése az éles ügyfél rendszerben
 - Csalásfelderítő eszköz
- OTP
 - Gépi tanulási eljárások alkalmazásában elnyert tender
 - Orosz, Román ügyfelekre hitelnemfizetés, hitelkártya viselkedés modellezés
 - 9Md tranzakció hálózatában kockázat-terjedés modellezés
- Ericsson
 - Mobil session drop, Quality of Experience predikció
 - Data Streaming analitika, világméretű IoT Data Hub prototípus
- Bosch
 - Gyártósori szenzor adatok alapján minőségi problémák előrejelzése, root cause analízis
- Telekom, Vodafone, Clickshop: kereső technológia

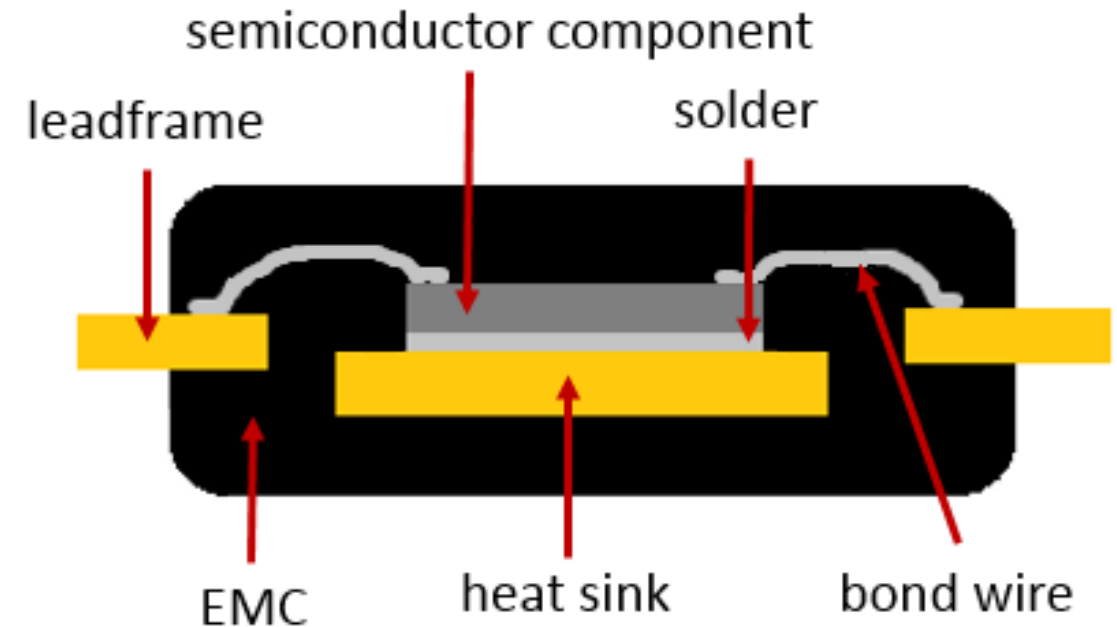




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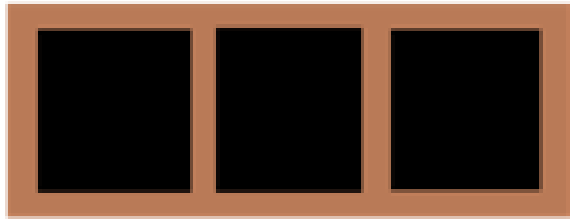
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Use case 1: scrap rate prediction in transfer molding

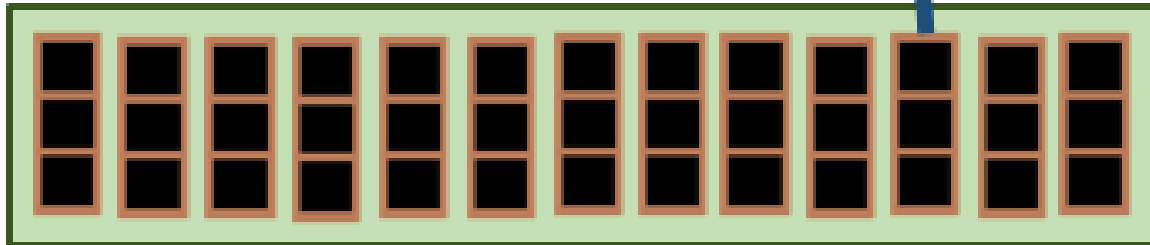


Cleaning cycles

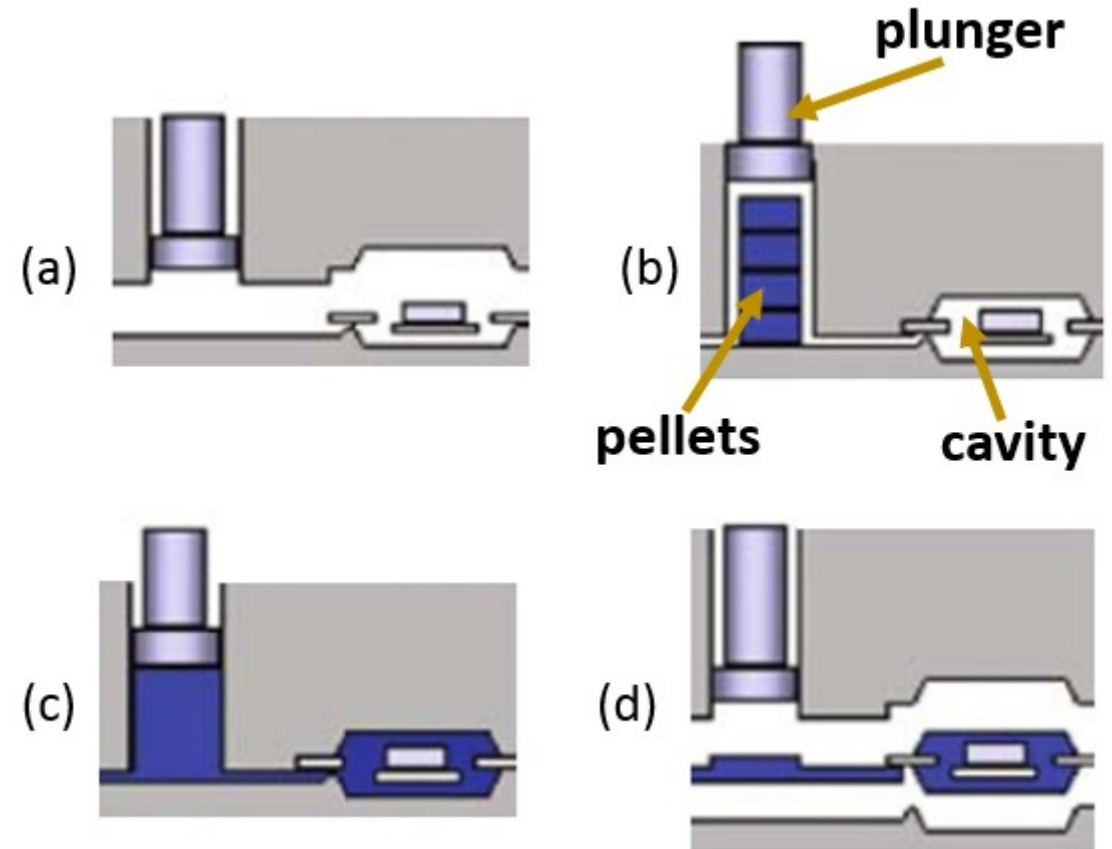
1 leadframe = 3 products



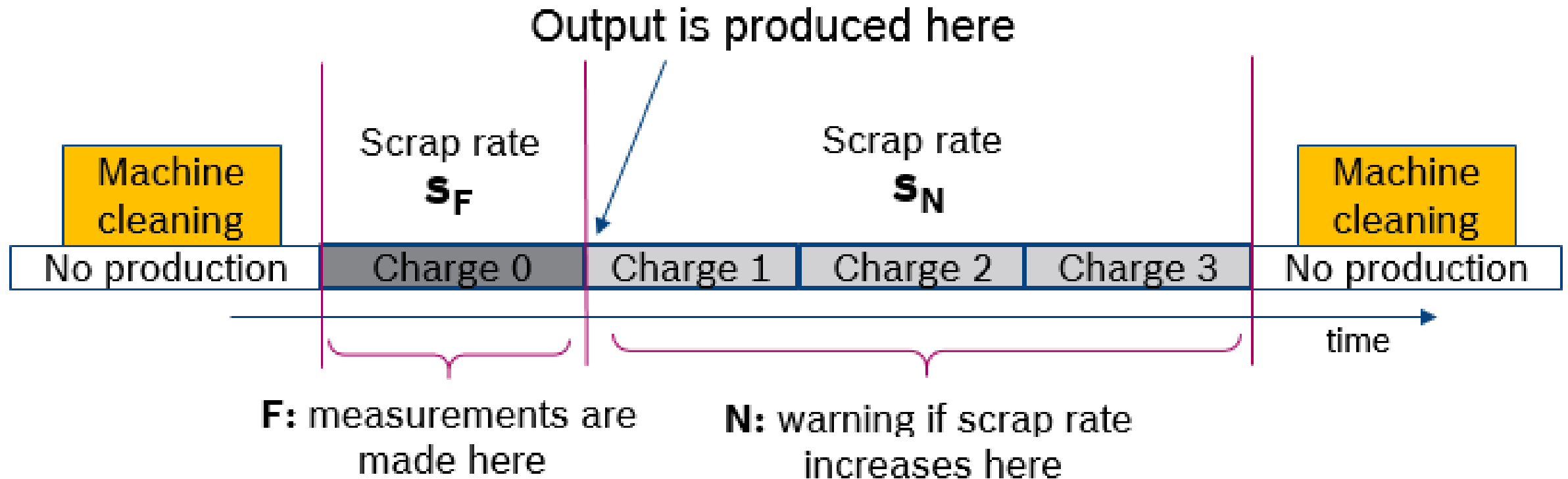
1 charge = 96 leadframes



1 cleaning cycle = 4-5 charges

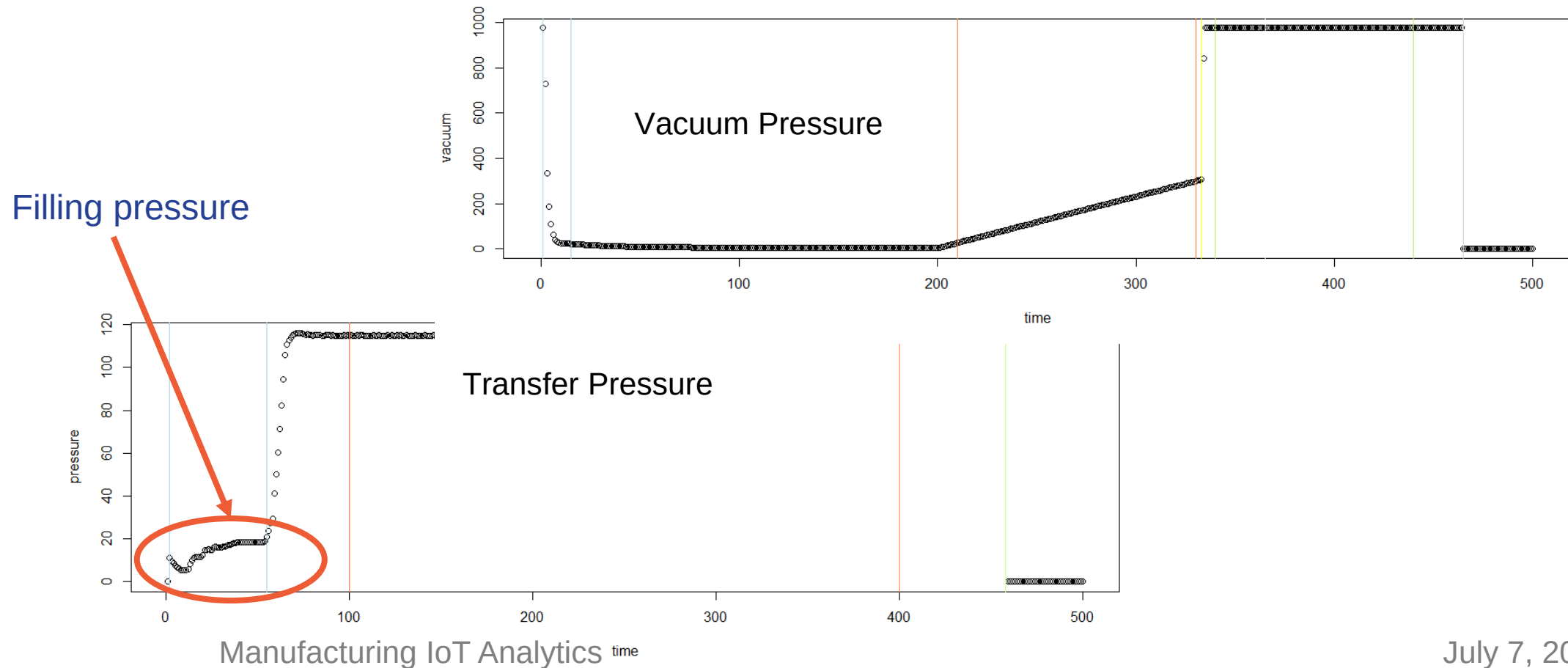


Scrap rate prediction task

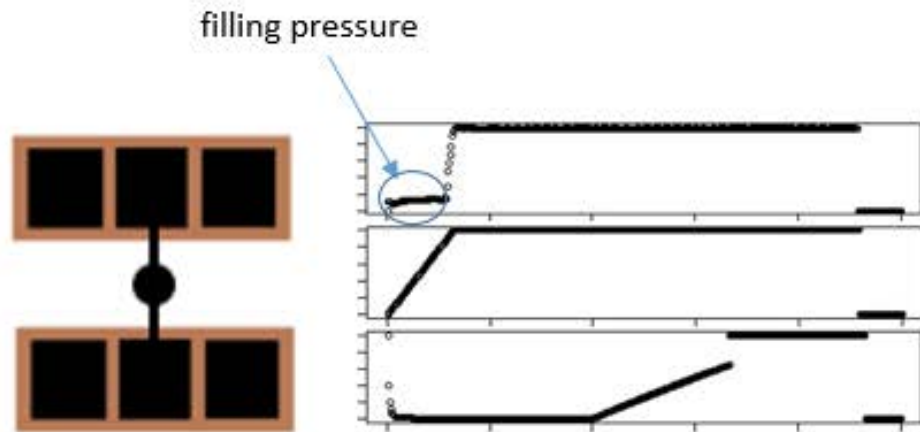


Data

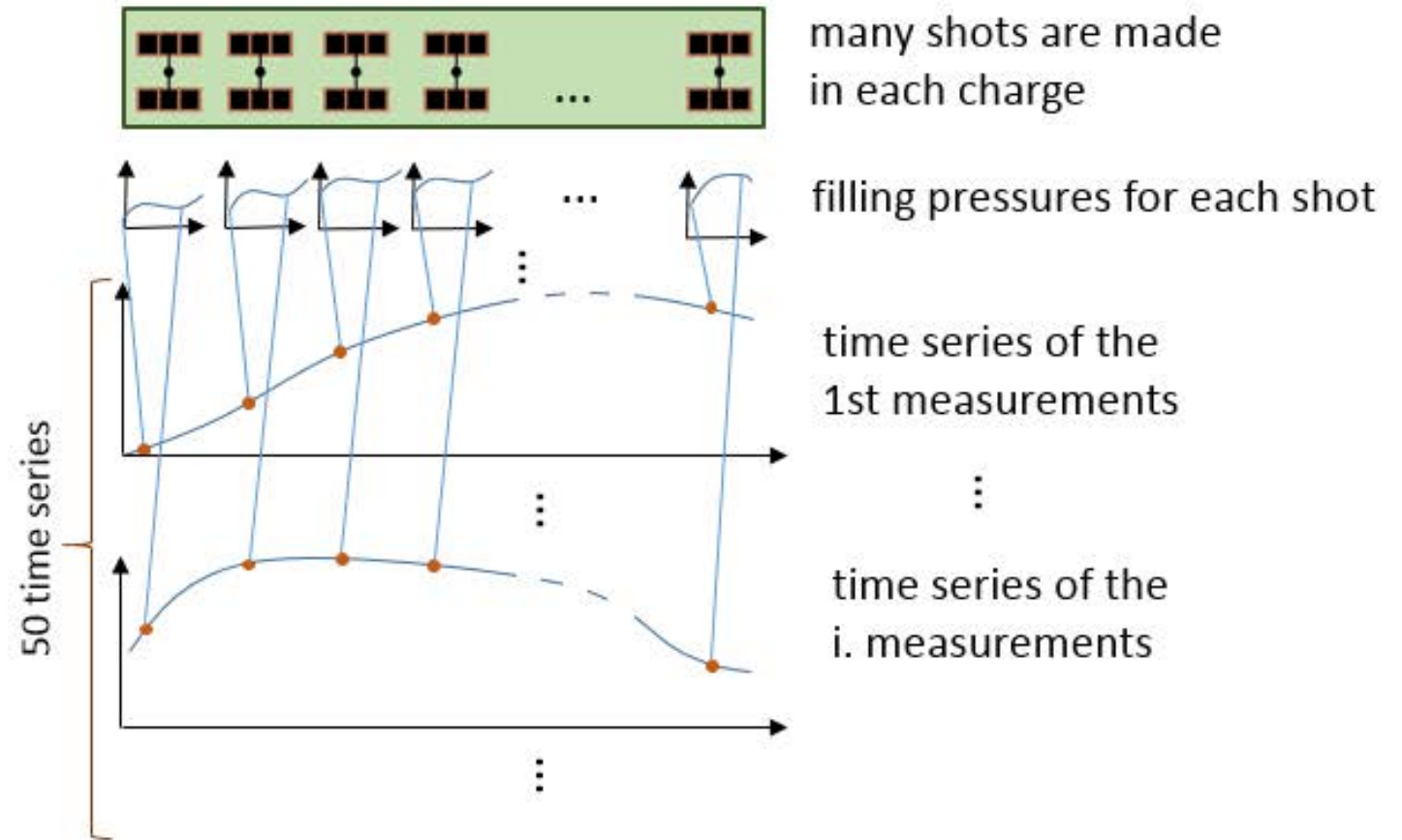
- Multiple time series, 500+ measurements in each: many, many data points
- Features of mean, variance, differentials, distribution of transfer graph data points
- In the end, ~50 features in the final classification data



Time series of time series

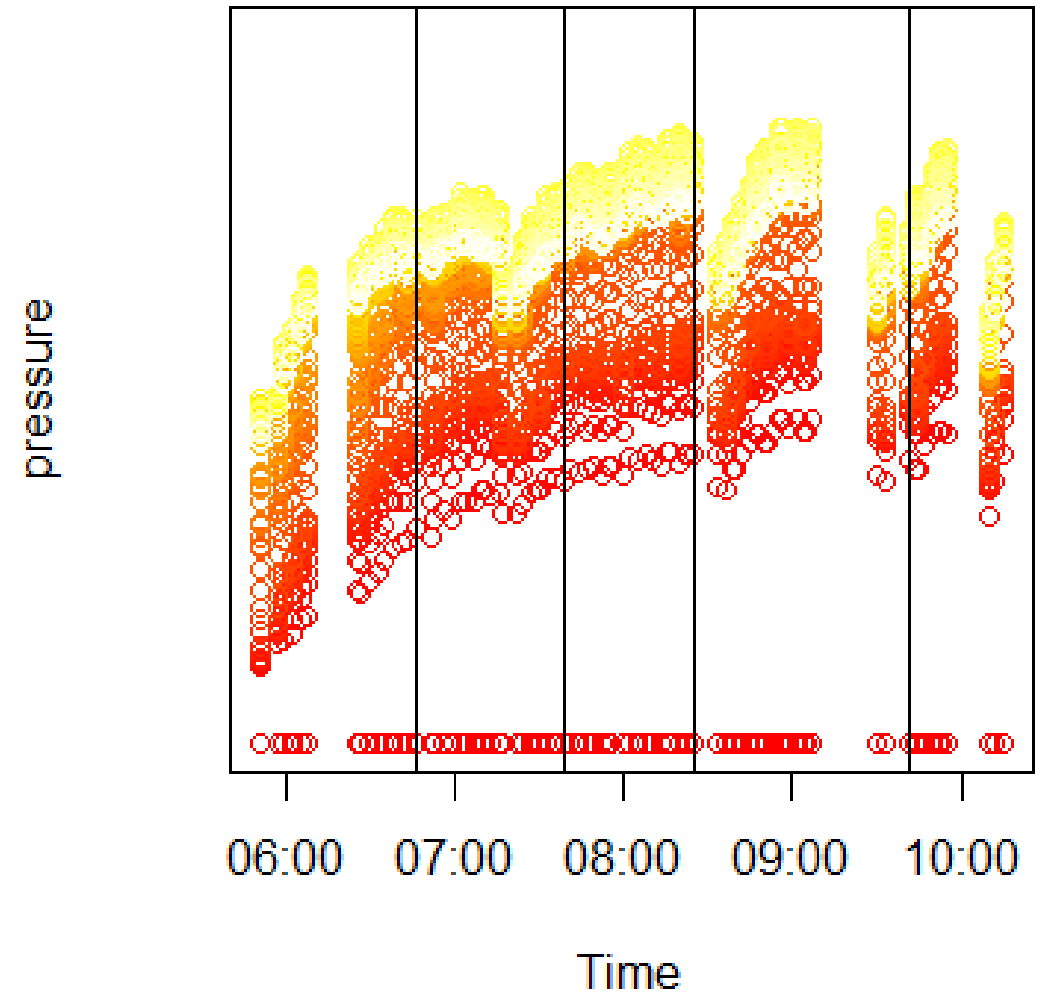


each shot 3 transfergraphs are recorded



Series of pressure series

- Filling pressure measurements
- Red to yellow color scale: measurement 1 – 50
- Vertical lines: new charges
- **Important to notice**
 - Values are lower after machine cleaning, and later they typically increase
 - Pressure is indirectly measured on the plunger
 - Contamination modifies pressure measurement



Summary

Facts:

6-10,000 products/hour
Few 100 data points per product
100> failed products in a day

Available for several months:

Delamination, Void, ... failures

- First line reject
- Second line reject
- Failures at later stages

Machine logs

- BottomPreheatTemperature1-6
- BottomToolTemperature
- UpperToolTemperature
- LoaderTemperature
- PreheatTime
- toolData[1-2].value
- TransferPressGraphPos1-150
- TransferSpeed1-10
- TransferTime
- TransferVacuum

Root Cause Analysis

Transfer pressure measured indirectly

- includes friction from valves
- certain points in the time series indicate contamination

Vacuum pressure has no direct effect, but ...

- Differences in trays: calibration problems
- Vacuum drop speed: leakage and blinding
- May result in less effective cleaning?

Result in variables that affect the production in indirect way that needs to be understood



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Use Case 2: Mobile radio session drop

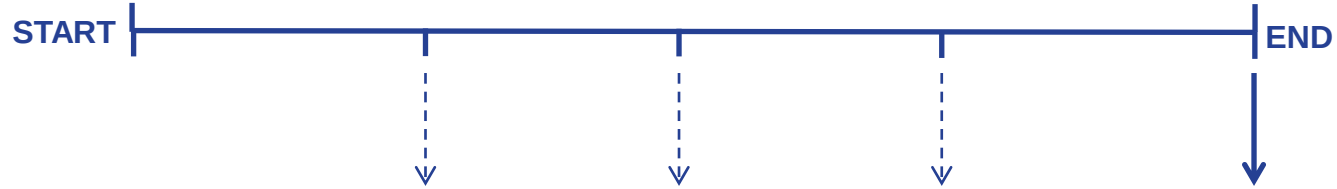
ERICSSON



Data is based on eNodeB CELLTRACE logs from a live LTE (4G) network

RRC connection setup /
Successful handover into the cell

UE context release/
Successful handover out of the cell

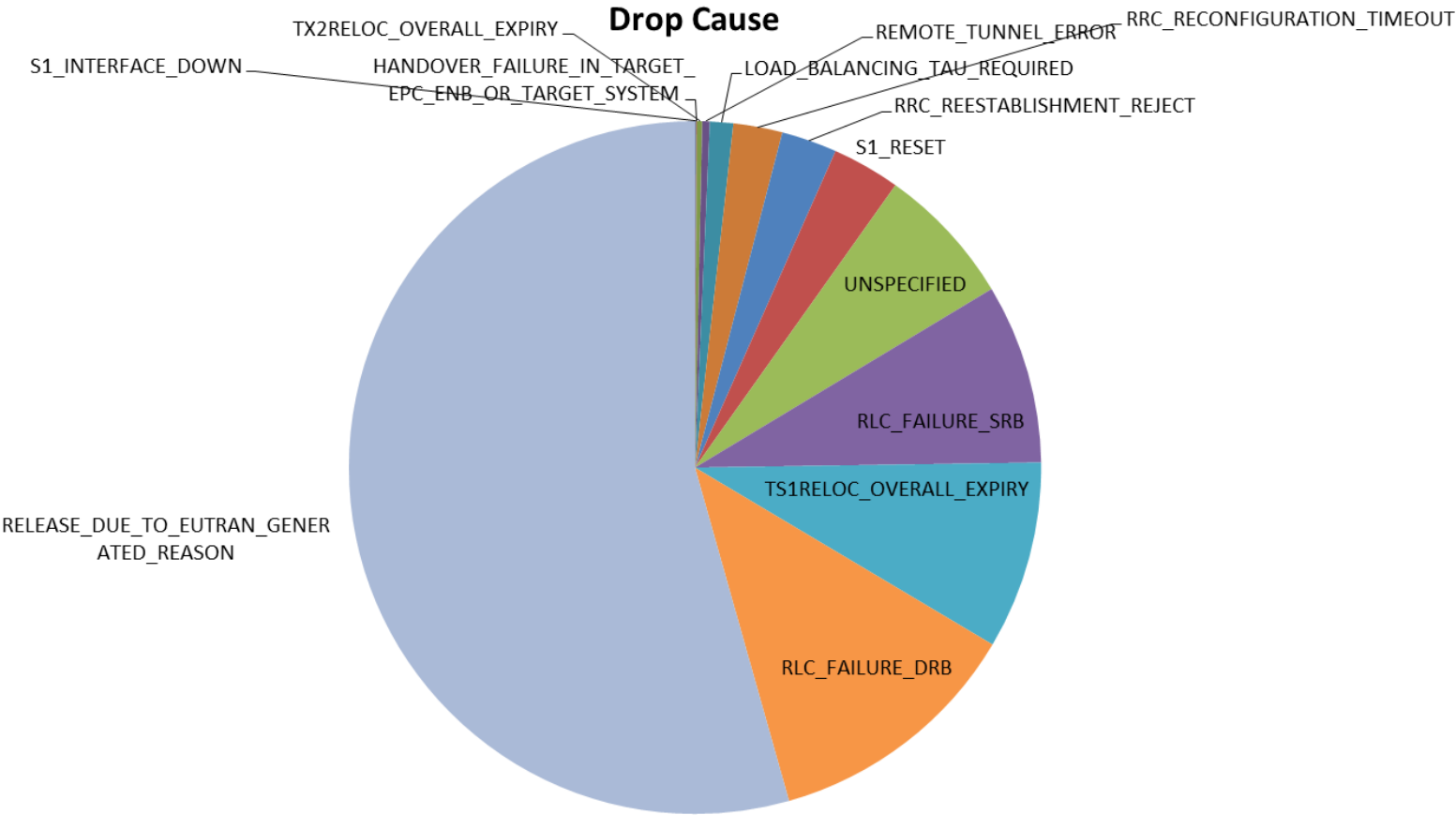
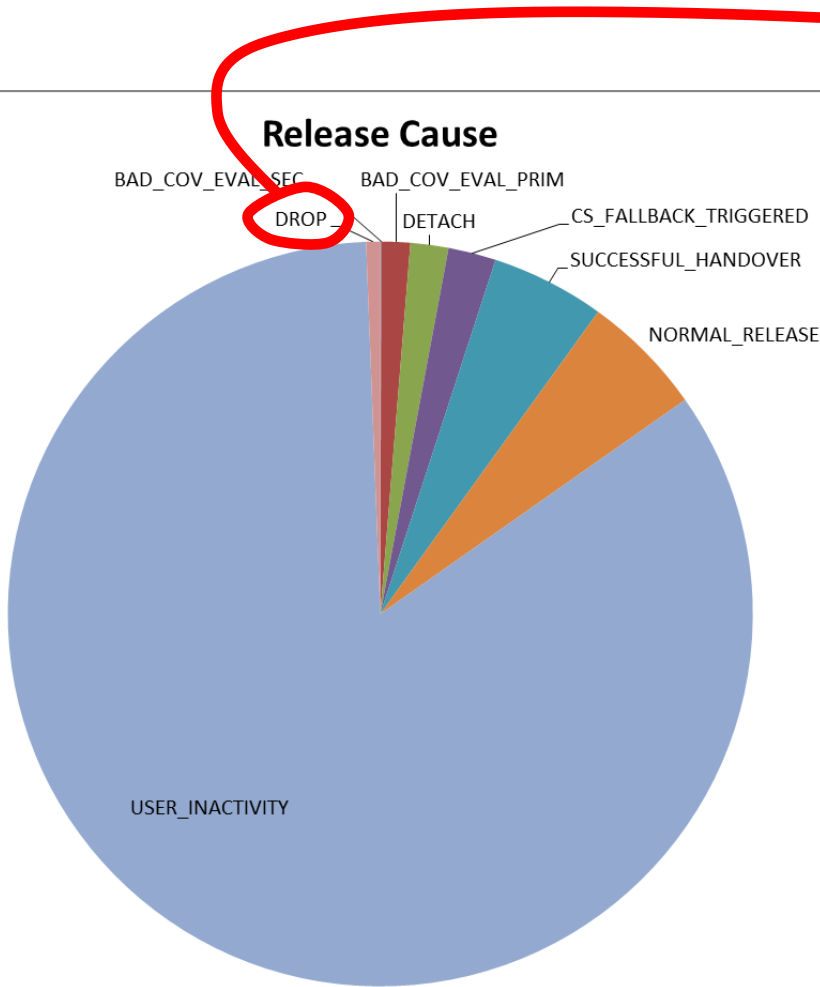


Per UE measurement reports
(RSRP, neighbor cell RSRP list)
Configurable period
Not available in this analysis

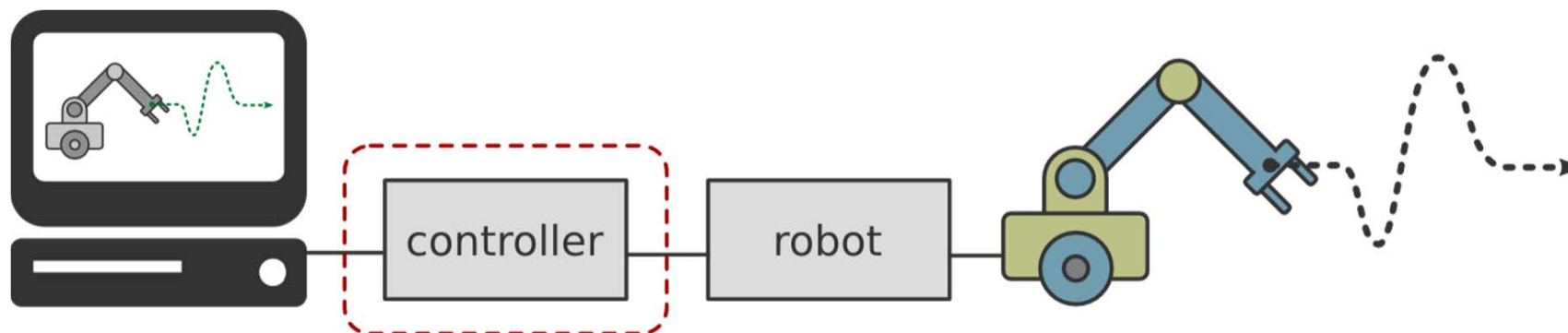
Per UE traffic report
(traffic volumes, protocol events (HARQ, RLC))
Per radio UE measurement
(CQI, SINR)
Period: 1.28s

Root-cause analysis: Cause of Release and Drop

0.6% of sessions are dropped



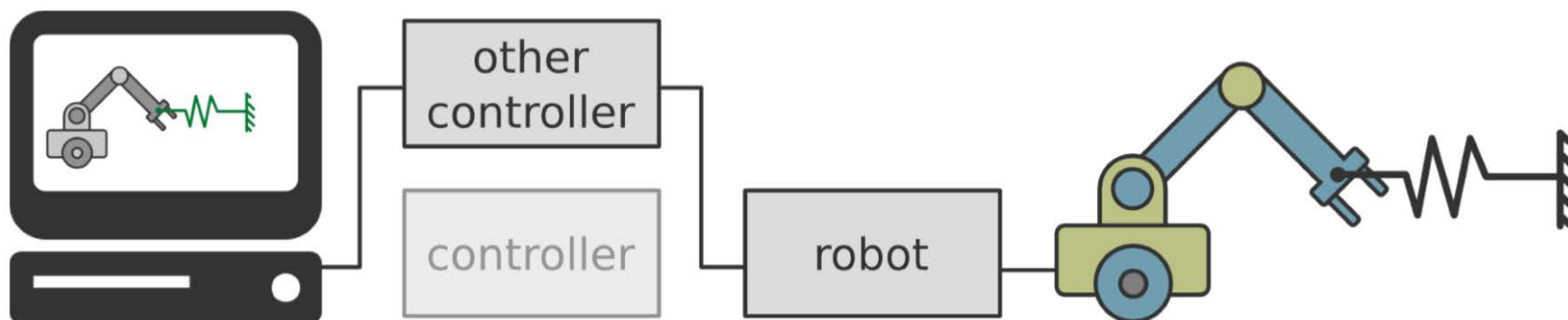
Latency critical communication with unreliable links



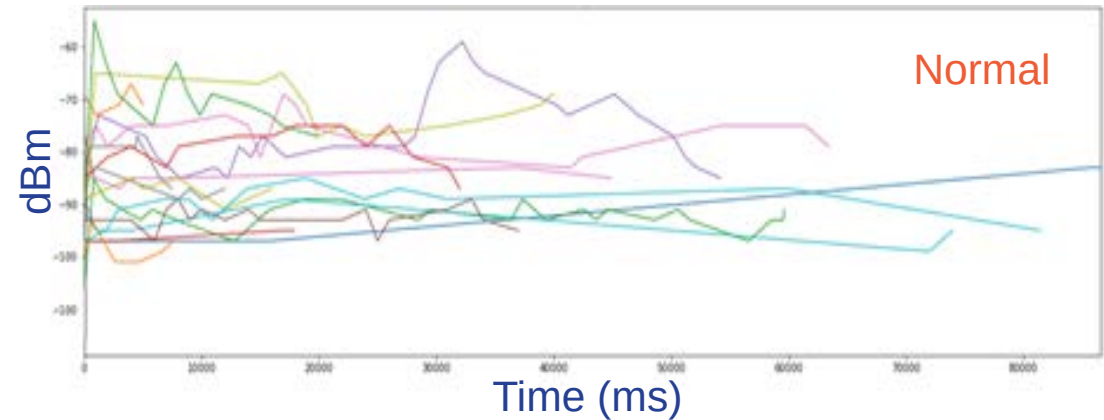
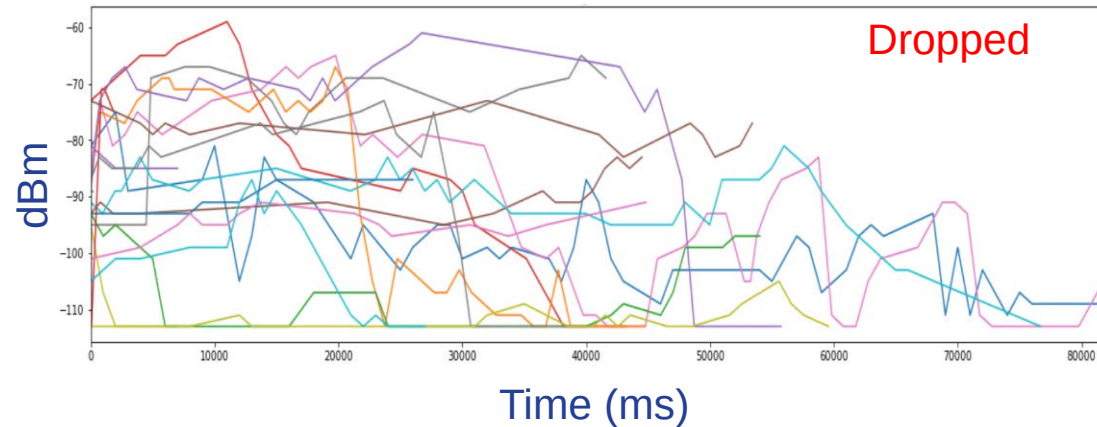
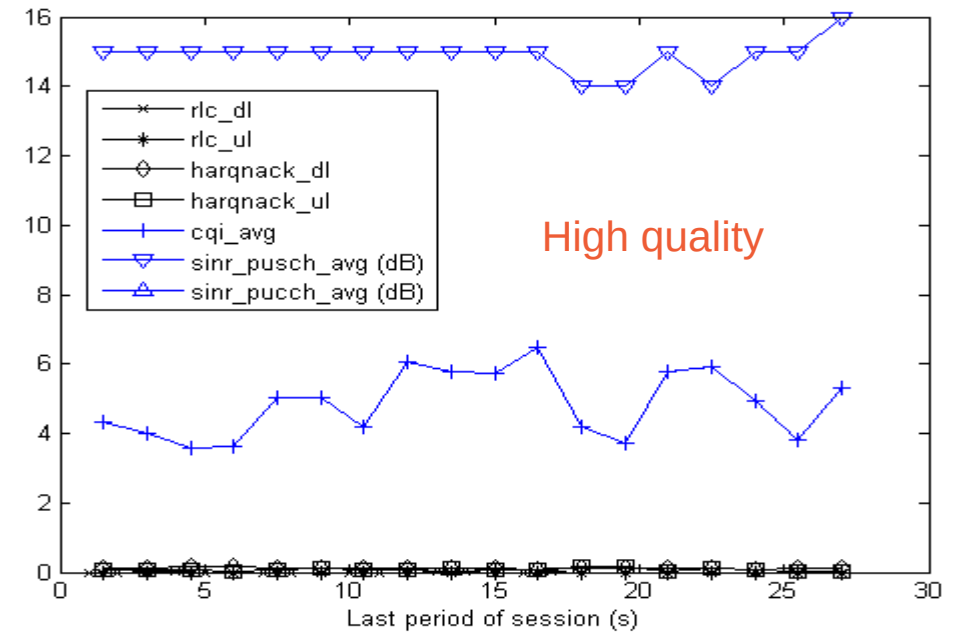
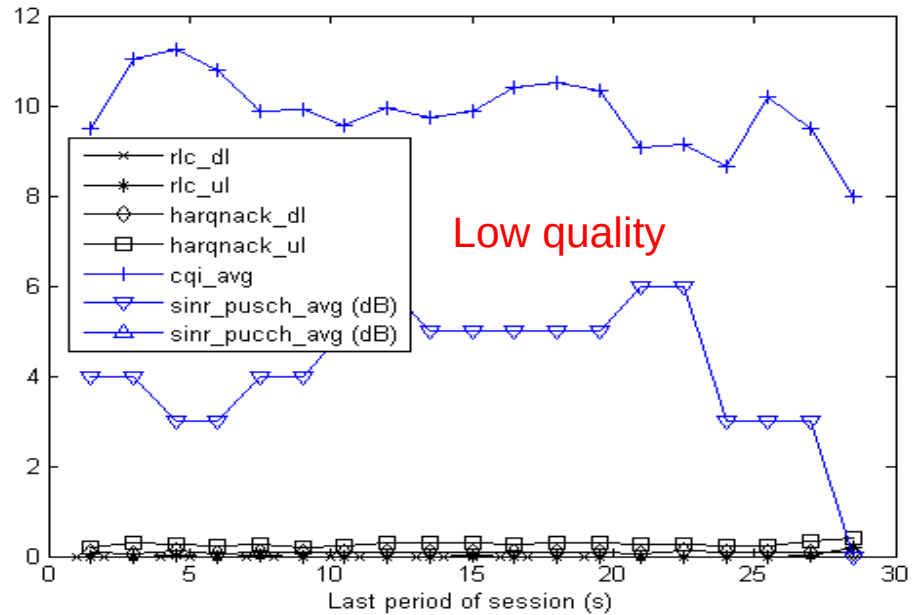
Detect network issues, predict problems ahead in time to prepare alternate control route

Make stable and reliable re-routing decisions in case of jitter

Reroute traffic for robot control and other real time applications



Examples for low quality and loss





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Use case 2 B: Session (call) drop by Smartphone logs



- Csaba Sidló
- Mátyás Susits
- Barnabás Balázs



Logging app and time series sample for illustration

82% 16:42

CellpredictRecorder

START LOGGING

STOP LOGGING

Logging

☒ subscription

☒ power

☒ network

☐ ping testing

☒ other sensors

☒ location

☒ CPU temp.

Prediction

☒ call drop

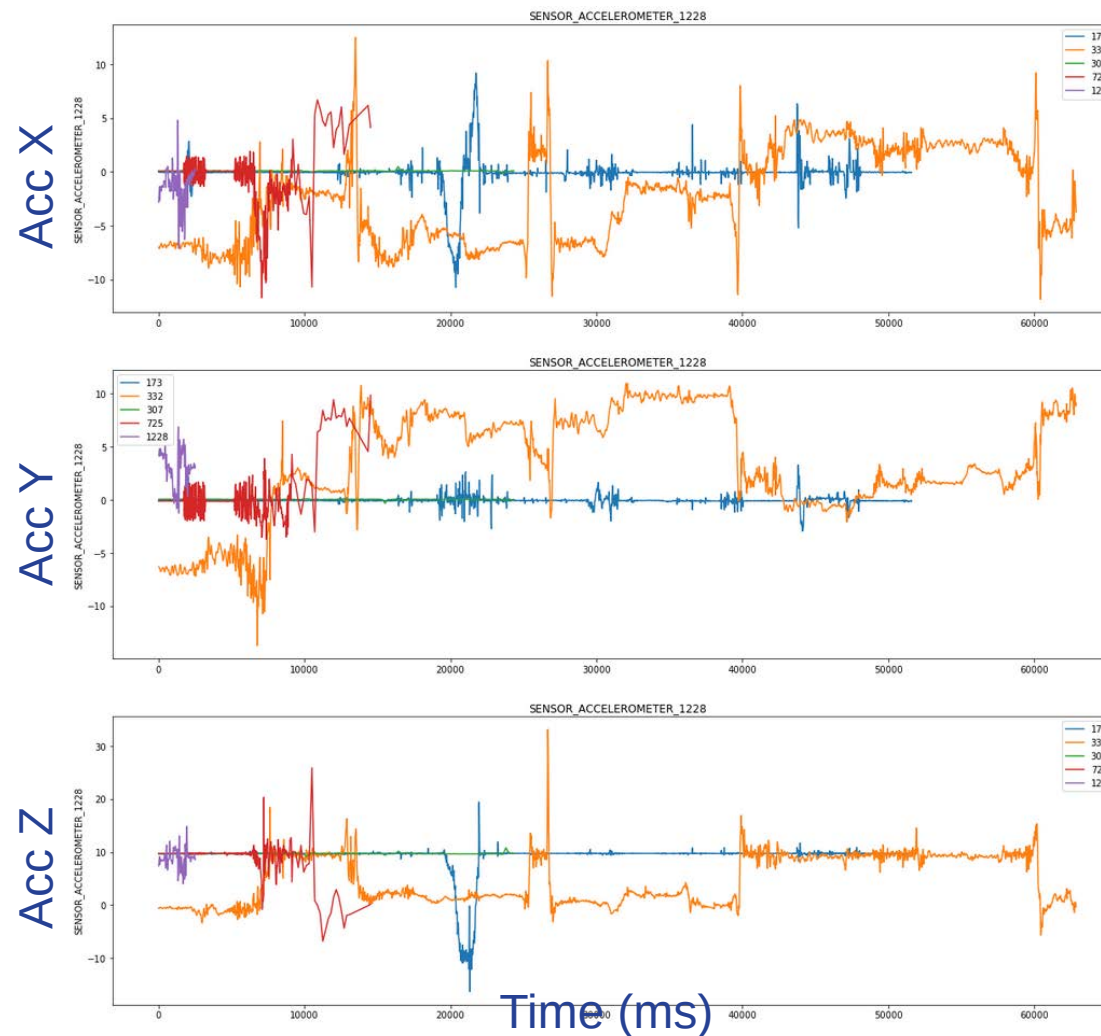
CLOSE APP

UPLOAD DATA

POWER SAVING SETTINGS

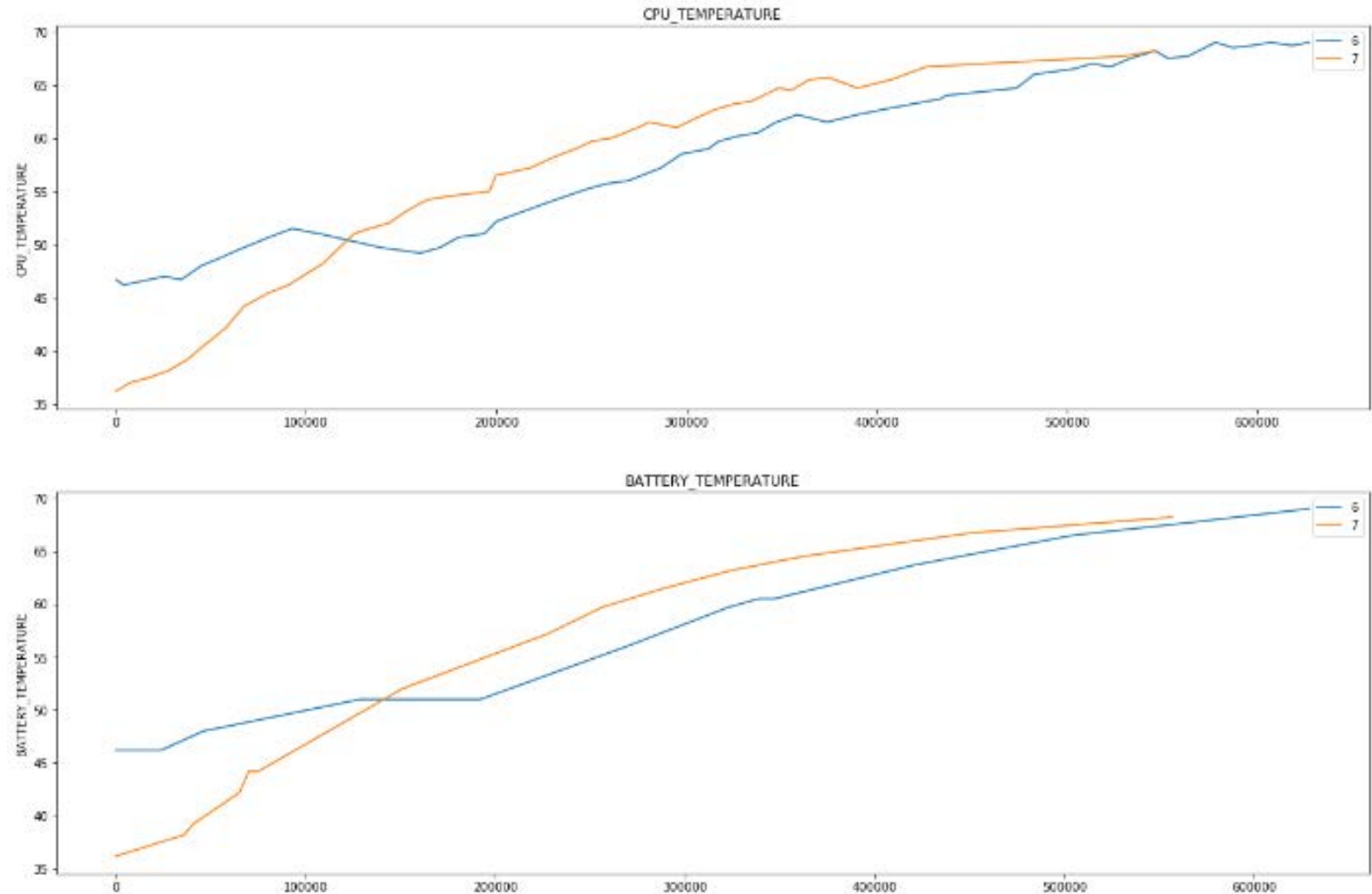
REQUEST PERMISSIONS

Accelerometer, 5 different devices



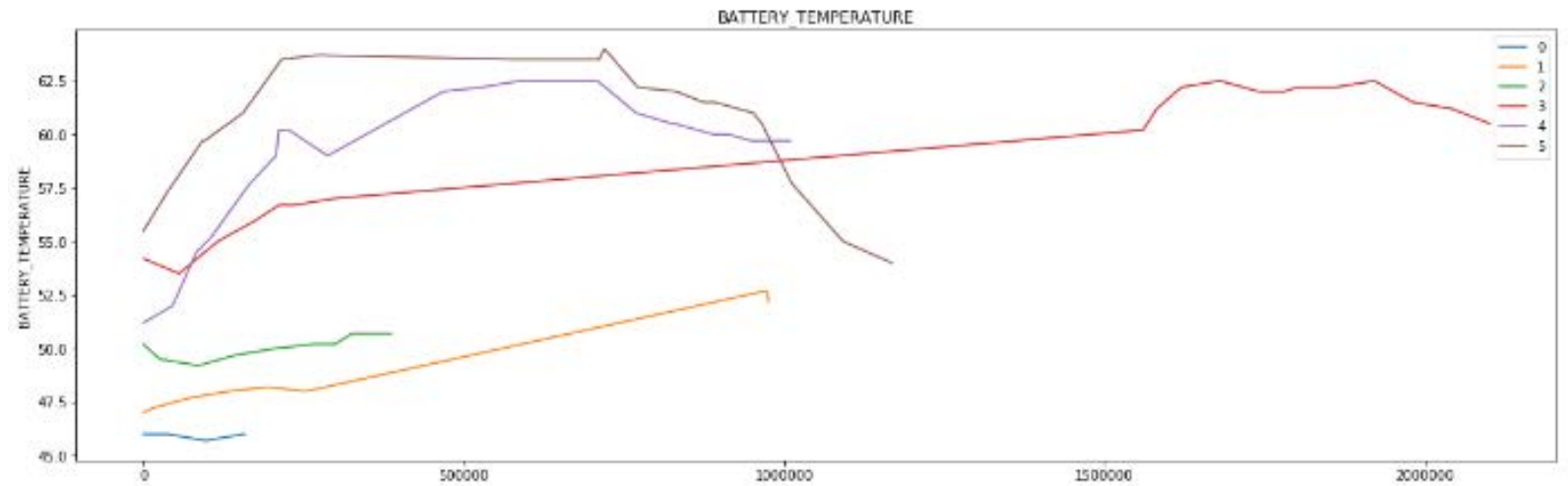
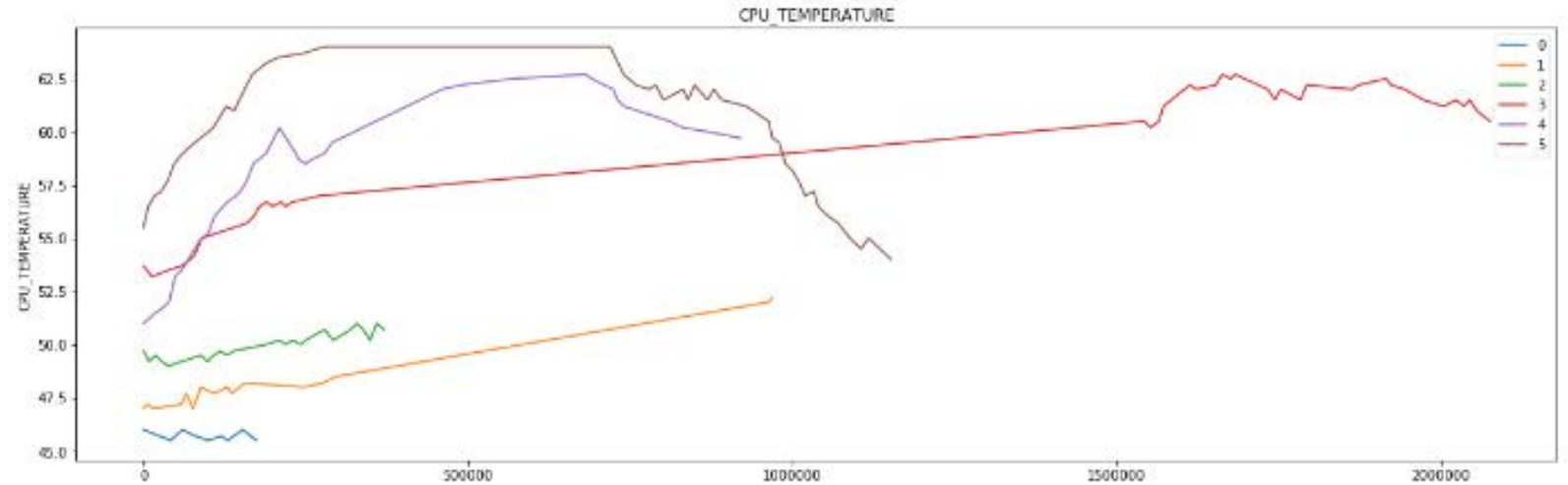
Overheated phone test until turn off

Heating until drop
(by CPU load + lamp)
Drop at 70C



Overheated phone test until turn off

Normal calls
still up to 65C



감사합니다!
Thank You!
תודה!



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Kérdések?